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Impact of Employees' Mental Health on Organisational Productivity in Multinational Corporations: An Empirical Study with Reference to Telangana State

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Abstract

In India's knowledge economy, mental health now ranks among the most important, and least managed, factors shaping how well the workforce performs. Telangana, and Hyderabad above all, is home to a large cluster of multinational corporations (MNCs) and global capability centres, where employees deal with constant cognitive load, schedules that span time zones and demanding performance targets. Even so, few studies in the Indian MNC context have examined, in structural terms, how employees' mental health turns into organisational productivity or how it erodes it. Building on the dual-continua model of mental health and the Job Demands–Resources (JD–R) theory, this study analyses two things together: (i) the relationships among two dimensions of mental health (positive mental health and psychological distress), work engagement and two productivity outcomes (individual work productivity and organisational productivity); and (ii) the direct and indirect effects of mental health on productivity through work engagement. A structured questionnaire was administered to 200 employees of MNCs in the Hyderabad, Rangareddy and Medchal–Malkajgiri districts of Telangana. The data were analysed through exploratory factor analysis, confirmatory factor analysis and Structural Equation Modelling (SEM) with the Maximum Likelihood Estimation (MLE) method, and mediation was tested with bias-corrected bootstrapping. The measurement analysis supported a five-construct model with good fit (CMIN/DF = 1.088, RMSEA = 0.021, CFI = 0.980). Positive mental health was a significant positive predictor of work engagement ($\beta = 0.355$, $p < 0.001$), while psychological distress lowered it significantly ($\beta = -0.424$, $p < 0.001$). Work engagement in turn raised both individual work productivity ($\beta = 0.259$, $p < 0.05$) and organisational productivity ($\beta = 0.250$, $p < 0.05$). Positive mental health also had a direct positive effect on individual work productivity ($\beta = 0.309$, $p < 0.01$). However, neither mental health dimension affected organisational productivity directly, and psychological distress had no direct effect on individual work productivity. The bootstrapped indirect effects showed that work engagement partially mediated the effect of positive mental health on individual work productivity and fully mediated the remaining three mental health–productivity relationships. The model accounted for 43.0% of the variance in work engagement, 29.6% in individual work productivity and 14.4% in organisational productivity. These results suggest that poor mental health costs MNCs productivity mainly by reducing engagement, and that spending on employee mental health should be seen as a productivity strategy and not as a welfare expense.

Keywords: Mental health; Psychological distress; Positive mental health; Burnout; Work engagement; Employee productivity; Organisational productivity; Multinational corporations; Telangana; Structural equation modelling; Human resource management

1. Introduction

Mental health can no longer be treated as a side issue for occupational health, because it sits at the heart of how organisations perform. According to the World Health Organization, depression and anxiety alone cost the world about 12 billion working days each year, which amounts to nearly US$1 trillion in lost productivity (WHO & ILO, 2022). Earlier economic modelling had shown that each dollar spent on scaling up treatment for common mental disorders returns roughly four dollars through better health and productivity (Chisholm et al., 2016). Poor mental health reduces productivity in two well-documented ways. The first is absenteeism, or the time employees spend away from work. The second is presenteeism, the lower output of employees who come to work but are psychologically impaired (Johns, 2010; Goetzel et al., 2004). Presenteeism is usually the larger of the two costs, and also the harder one to see (de Oliveira et al., 2023).

A large part of this burden falls on India. The National Mental Health Survey (2015–16) reported that about one in ten adults had a current mental morbidity, and that the treatment gap was above 70 per cent for most disorders (Gautham et al., 2020). Deloitte's (2022) national workplace survey put the annual cost of poor employee mental health to Indian employers at about US$14 billion, arising from absenteeism, presenteeism and attrition. Within the Indian workforce, people employed in information technology (IT), IT-enabled services and other knowledge-intensive MNCs have been singled out again and again as a high-risk group. The reasons include long working hours, deadlines set by clients, night shifts that follow overseas markets, job insecurity and a digital culture that is always switched on (Darshan et al., 2013; Rao & Chandraiah, 2012; Padma et al., 2015).

Telangana offers a highly relevant setting for this study. Hyderabad has become one of the main destinations in India for MNC investment, with large campuses and global capability centres in technology, banking and financial services, pharmaceuticals and life sciences. In 2023–24, the state's IT exports were about ₹2.68 lakh crore, and the sector employed more than nine lakh professionals (Government of Telangana, 2024). How productive this workforce is thus matters for individual firms and for the state's economy as a whole. Yet the fast growth of MNC employment in Telangana has not been accompanied by systematic research on how employees' mental health shapes the productivity of their organisations.

Existing studies have three shortcomings. To begin with, most research on Indian corporate employees reports how common stress or burnout is, but does not go on to connect mental health with outcomes at the level of the organisation. Next, mental health has mostly been measured either as the absence of illness (distress, burnout, anxiety) or as the presence of well-being, and only rarely as both. The dual-continua model (Keyes, 2002, 2005) holds that these are related yet distinct dimensions; an employee may be free of distress without flourishing, and the reverse is also possible. Lastly, the psychological mechanism that turns mental health into productive effort has seldom been tested. Work engagement, a positive, fulfilling state marked by vigour, dedication and absorption (Schaufeli et al., 2002), is a strong theoretical candidate for this mediating role, since it is known to be linked with both well-being and performance (Bakker & Demerouti, 2007; Christian et al., 2011).

For these reasons, and in line with the structural approach of recent behavioural modelling studies (e.g., Bayih & Singh, 2020), this study builds and tests a mental health–productivity model for MNC employees in Telangana. The study has four objectives: (i) to identify the underlying dimensions of positive mental health and psychological distress among MNC employees; (ii) to examine the direct effects of these two dimensions on work engagement, individual work productivity and organisational productivity; (iii) to examine how work engagement affects the two productivity outcomes; and (iv) to test whether work engagement mediates the relationships between mental health and productivity. Data from 200 MNC employees were analysed with the Maximum Likelihood Estimation (MLE) method of Structural Equation Modelling (SEM).

2. Review of literature

2.1. Employee mental health: a dual-continua perspective

The World Health Organization describes mental health as a state of mental well-being that allows people to cope with life's stresses, realise their abilities, learn and work well, and contribute to their community (WHO, 2022). The definition purposely covers the capacity to work productively, and this puts mental health at the centre of organisational behaviour. Keyes (2002) suggested that mental health and mental illness sit on two separate but correlated continua. The first, positive mental health, runs from languishing to flourishing. It is made up of emotional well-being (positive affect and life satisfaction), psychological well-being or functioning (self-acceptance, autonomy, purpose and mastery) and social well-being (belonging, contribution and social acceptance). The second continuum, psychological distress, reflects symptoms such as stress, anxiety, low mood and exhaustion (Keyes, 2005).

At work, psychological distress usually shows up as occupational stress, anxiety and depressive symptoms, and burnout. Occupational stress occurs when people see the demands of their job as greater than the resources they have (Cohen et al., 1983; Hobfoll, 1989). Anxiety and low mood are the most common mental disorders in the working population, and non-clinical surveys measure them with screening tools such as the DASS and K10 (Lovibond & Lovibond, 1995; Kessler et al., 2003a). Burnout is a syndrome specific to work, involving exhaustion, cynicism and reduced efficacy, which develops after long exposure to job stressors (Maslach et al., 2001; Kristensen et al., 2005). In Indian IT and MNC settings, the three often appear together. Darshan et al. (2013) observed high professional stress and depressive symptoms among IT professionals in Bengaluru, and Rao and Chandraiah (2012) found that occupational stress significantly harmed the mental health of IT professionals in Hyderabad. On this basis, the present study treats psychological distress as a higher-order construct with three first-order dimensions (occupational stress, anxiety and low mood, and burnout). Positive mental health is likewise treated as a higher-order construct with three first-order dimensions (emotional, psychological and social well-being).

2.2. Work engagement

Work engagement refers to a positive, fulfilling, work-related state of mind marked by vigour, dedication and absorption (Schaufeli et al., 2002). Vigour means having high energy and mental resilience while working. Dedication means feeling a sense of significance, enthusiasm and pride. Absorption means being fully concentrated on, and happily engrossed in, one's work (Schaufeli et al., 2006). Kahn (1990) had earlier described engagement as harnessing the self to work roles, a process that depends on psychological meaningfulness, safety and availability. The third condition, psychological availability, ties directly to mental health, because employees who feel emotionally drained or anxious have fewer personal resources to put into their roles. In JD–R theory, engagement is the main outcome of the motivational process, which is driven by job and personal resources, whereas burnout results from the health-impairment process, which is driven by job demands (Bakker & Demerouti, 2007, 2017; Schaufeli & Bakker, 2004).

2.3. Individual and organisational productivity

Workplace productivity can be understood at two levels. Individual work productivity deals with the quantity, quality and timeliness of an employee's work, along with the ability to stay focused on the task, and it is closely tied to task performance (Koopmans et al., 2014). Self-report tools such as the WHO Health and Work Performance Questionnaire capture it by asking employees to rate their own output and concentration against what is expected of them (Kessler et al., 2003b). Organisational productivity is the efficiency and effectiveness with which a work unit or organisation turns its human resources into outputs. It shows in meeting output targets, delivering to clients on time, keeping absenteeism low and improving overall efficiency (Harter et al., 2002). Since objective organisation-level data are seldom available for individual respondents, studies of employee attitudes often rely on employees' perceptions of team and organisational performance as a proxy (Harter et al., 2002; Salanova et al., 2005). The two outcomes are linked but conceptually different. Following Bayih and Singh (2020), who kept two forms of behavioural intention apart, this study treats them as separate constructs.

2.4. Relationships among mental health, work engagement and productivity

Prior research points to four paths: from mental health directly to work engagement; from mental health directly to productivity; from work engagement directly to productivity; and from mental health to productivity indirectly through

work engagement. On the first path, the broaden-and-build theory suggests that positive emotions broaden employees' thought–action repertoires and help them build lasting personal resources (Fredrickson, 2001). These resources provide the energy and dedication that make up engagement. Empirical work confirms that psychological well-being is a robust antecedent of engagement (Robertson et al., 2012; Shuck & Reio, 2014). On the other side, the conservation of resources theory (Hobfoll, 1989) and the health-impairment process of the JD–R model both predict that stress, anxiety and exhaustion drain the resources that engagement needs. Longitudinal studies show that burnout and depressive symptoms lower later engagement (Hakanen et al., 2008), and burnout and engagement are consistently found to be negatively related (Bakker et al., 2014).

H1. *Positive mental health has a significant positive relationship with the work engagement of MNC employees.*

H2. *Psychological distress has a significant negative relationship with the work engagement of MNC employees.*

Mental health is also likely to influence productivity directly. Wright and Cropanzano (2000, 2004) found that psychological well-being predicted supervisors' ratings of job performance even after job satisfaction was taken into account. In a meta-analysis, Ford et al. (2011) reported that psychological health, covering both well-being and the absence of distress, was one of the strongest health correlates of work performance. Distress, on the other hand, cuts productivity through absenteeism and, to a greater extent, through presenteeism (Johns, 2010; Darr & Johns, 2008). Bubonya et al. (2017) showed that employees in poor mental health were absent more often and rated their own productivity lower, and Taris (2006) found that burnout, particularly exhaustion, was negatively associated with objective performance. Most of this evidence relates to individual-level performance, but a smaller body of work connects aggregate employee well-being and absence of distress with unit-level outcomes such as productivity and profitability (Harter et al., 2002; LaMontagne et al., 2014). Still, the size of the direct effects differs from one study and setting to another, so it is reasonable to test them separately for each outcome.

H3. *Positive mental health has a significant positive relationship with the individual work productivity of MNC employees.*

H4. *Positive mental health has a significant positive relationship with organisational productivity.*

H5. *Psychological distress has a significant negative relationship with the individual work productivity of MNC employees.*

H6. *Psychological distress has a significant negative relationship with organisational productivity.*

In organisational research, work engagement is one of the most consistent predictors of performance. Christian et al. (2011), in their meta-analysis, found that engagement predicted task and contextual performance beyond what job attitudes explained, and Rich et al. (2010) showed that engagement mediated the effects of value congruence and perceived support on performance. Engaged employees have been found to produce higher financial returns (Xanthopoulou et al., 2009), better weekly performance (Bakker & Bal, 2010) and stronger in-role performance (Halbesleben & Wheeler, 2008). At the unit level, Harter et al. (2002) reported that business units with higher engagement also had higher productivity, profitability and customer satisfaction, and Salanova et al. (2005) connected collective engagement with service performance. Saks (2006) also confirmed that engagement mediates between organisational antecedents and work outcomes.

H7. *Work engagement has a significant positive relationship with the individual work productivity of MNC employees.*

H8. *Work engagement has a significant positive relationship with organisational productivity.*

Read together, these lines of research suggest that work engagement carries the effects of mental health through to productivity. In the JD–R framework, personal resources such as positive mental health encourage engagement, and engagement then leads to performance (the motivational process). Strain such as burnout, by contrast, lowers engagement and so lowers performance (Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004). Robertson et al. (2012) found that psychological well-being improved the explanation of the engagement–performance relationship, and Shuck and Reio (2014) reported that engagement and well-being work together in predicting work outcomes.

The review nonetheless revealed several research gaps. First, nearly all studies connecting mental health with productivity come from Western countries, and Indian studies of MNC employees have looked at how widespread stress

is rather than at what it does to organisations. Second, earlier research has mostly measured mental health as either distress or well-being, which runs against the dual-continua model. Third, even though productivity can be observed at both individual and organisational levels, studies seldom examine the two outcomes in a single structural model. Finally, no study has structurally examined the mediating role of work engagement between both dimensions of mental health and both productivity outcomes among MNC employees in Telangana. Figure 1 presents the theoretical model of the study.

H9. *The relationship between positive mental health and individual work productivity is mediated by work engagement.*

H10. *The relationship between positive mental health and organisational productivity is mediated by work engagement.*

H11. *The relationship between psychological distress and individual work productivity is mediated by work engagement.*

H12. *The relationship between psychological distress and organisational productivity is mediated by work engagement.*

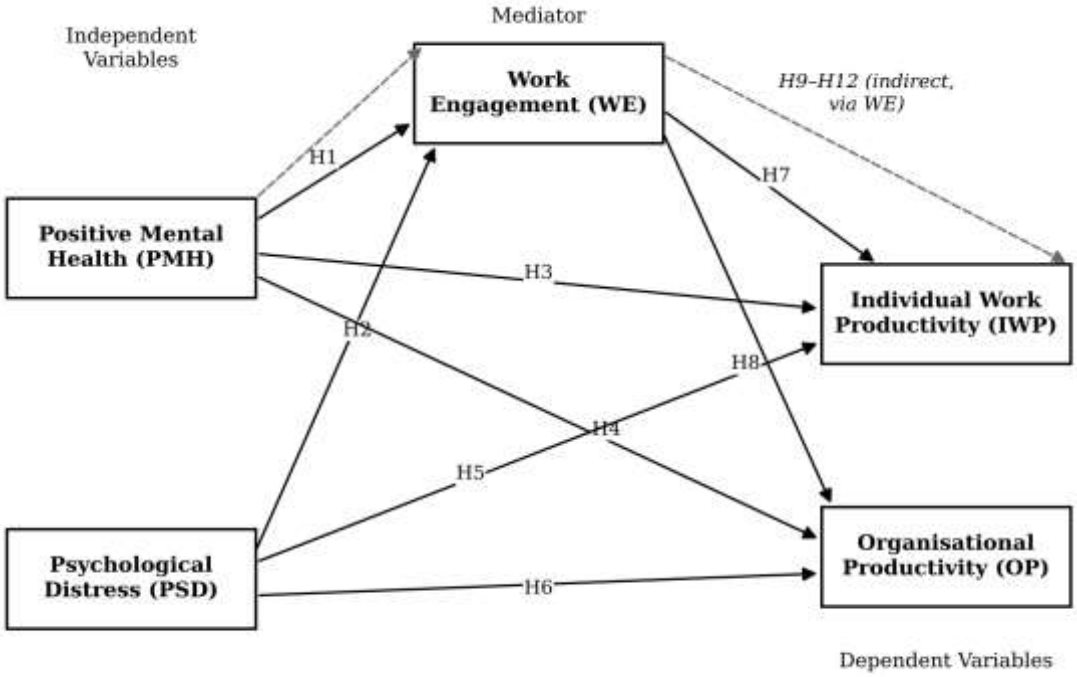


Figure 1. Theoretical model. Solid arrows denote direct effects (H1–H8); dashed arrows denote indirect effects via work engagement (H9–H12).

3. Research methods

3.1. Study area description

The study was carried out in Telangana, a southern Indian state created in 2014 with Hyderabad as its capital. The state has an area of about 1.12 lakh square kilometres and is divided into 33 districts for administration. Most MNC activity in the state is concentrated in the Hyderabad Metropolitan Region, especially along the western technology corridor of HITEC City, Madhapur, Gachibowli, Nanakramguda and the Financial District, an area that falls within the Hyderabad, Rangareddy and Medchal–Malkajgiri districts. The region has large campuses and global capability centres of multinational firms in technology, banking and financial services, consulting, pharmaceuticals and life sciences, and the Genome Valley life-science cluster is located on the northern edge of the city. With IT exports of about ₹2.68 lakh crore in 2023–24 and more than nine lakh professionals working in the sector (Government of Telangana, 2024), the region provides a large and varied population of MNC employees. For this reason, the three districts were chosen as the study area.

3.2. Research design and approach

A cross-sectional, descriptive and explanatory (causal) research design was used, for three reasons. The first is that the study aims to give a full explanation of the relationships among employees' mental health, work engagement and productivity. The second is that the research questions and hypotheses were framed on the basis of established theory (the dual-continua model and JD–R theory) and empirical findings.

3.3. Sampling design and sample size determination

There is no publicly available complete list of MNC employees in Telangana, and reaching employees requires permission from their organisations, so a probability sampling frame could not be built. The study therefore used a multi-stage non-probability approach. At the first stage, the three districts with the highest concentration of MNC offices were selected purposively. At the second stage, MNCs were placed in four sectors: IT and IT-enabled services; banking, financial services and insurance (BFSI); pharmaceuticals and life sciences; and other sectors such as consulting, engineering and manufacturing. At the third stage, employees who had worked for at least six months in their present organisation were contacted through convenience and referral sampling, using professional networks and HR contacts, both in person and by an online form.

As for sample size, Roscoe's rule of thumb (cited in Sekaran & Bougie, 2016) holds that samples above 30 and below 500 suit most behavioural research. For SEM, Kline (2016) recommends at least 200 cases, while Hair et al. (2019) advise a minimum of five observations for each measured item; with 38 measurement items, this means at least 190 respondents. The final sample was accordingly set at 200 respondents. Questionnaires continued to be collected until, after incomplete and unusable returns had been screened out, 200 complete and valid responses were available, and all 200 were kept for analysis. The sector-wise distribution of the sample is given in Table 1A.

Table 1A. Sector-wise distribution of the sample.

Sector	**Valid responses**	**Percentage of sample**	**Cumulative percentage**
IT and IT-enabled services	99	49.5%	49.5%
BFSI	41	20.5%	70.0%
Pharmaceuticals and life sciences	29	14.5%	84.5%
Others (consulting, engineering, manufacturing)	31	15.5%	100.0%
Total	**200**	**100.0%**	–

Note: sector categories follow the MNC classification adopted in the second sampling stage.

3.4. Research instrument development

Primary data came only from a structured questionnaire, which was divided into two parts. Part A recorded the socio-demographic and job profile of the respondents. Part B measured the five latent constructs through 38 items rated on a five-point Likert scale, from strongly disagree (1) to strongly agree (5). Every item was adapted from a validated scale and reworded to fit the MNC context (see Appendix A).

Psychological distress was measured using 12 items spread across three dimensions, with four items in each. The occupational stress items came from the Perceived Stress Scale (Cohen et al., 1983); the anxiety and low mood items came from the DASS-21 and K10 screening scales (Lovibond & Lovibond, 1995; Kessler et al., 2003a); and the burnout items came from the Copenhagen Burnout Inventory and Maslach's conceptualisation (Kristensen et al., 2005; Maslach et al., 2001). These items describe symptoms, not diagnoses, and they were not used to classify anyone clinically. Positive mental health was measured using nine items across three dimensions (emotional, psychological and social well-being), adapted from the Mental Health Continuum–Short Form (Keyes, 2002, 2005). Work engagement was assessed with the nine-item Utrecht Work Engagement Scale (UWES-9), which covers vigour, dedication and absorption (Schaufeli et al., 2006). Individual work productivity was assessed with four items taken from the Individual Work Performance Questionnaire and the WHO Health and Work Performance Questionnaire (Koopmans et al., 2014; Kessler

et al., 2003b). Organisational productivity was assessed with four perceptual items on output targets, timely delivery, absenteeism and efficiency, adapted from Harter et al. (2002) and Salanova et al. (2005).

4. Methods of data analysis

The returned questionnaires were checked for completeness and suitability, then coded and entered for analysis. Data preparation included checks for missing values, outliers, normality and multicollinearity. The respondents' profile and their responses were summarised with descriptive statistics (frequencies, percentages, means, standard deviations, skewness and kurtosis). Exploratory Factor Analysis (EFA), using Principal Component Analysis with varimax rotation, was run to uncover the underlying factor structure, and Harman's single-factor test was applied to check for common method variance (Podsakoff et al., 2003). In keeping with the two-step approach of Anderson and Gerbing (1988), Confirmatory Factor Analysis (CFA) was then used to validate the measurement model by assessing reliability, convergent validity and discriminant validity. Two competing measurement models (eleven first-order dimensions versus five constructs) were compared using the chi-square difference test, and a dimension-level (parcelled) model was used to examine the higher-order structure of the mental health and engagement constructs (Little et al., 2002). The structural model was then estimated through the Maximum Likelihood Estimation method of SEM. Absolute, incremental and parsimony fit indices were used to judge model fit. Mediation was tested through the bias-corrected bootstrapping method with 5,000 resamples and 95% confidence intervals (Preacher & Hayes, 2008; Zhao et al., 2010). All analyses were run in Python 3. The pandas, SciPy and factor_analyzer libraries handled the descriptive, reliability and exploratory analyses, and the semopy package (Igolkina & Meshcheryakov, 2020) handled CFA and SEM; the Wishart maximum likelihood estimator in semopy is equivalent to the default ML estimator in covariance-based programs such as IBM SPSS AMOS.

5. Findings

5.1. Socio-demographic characteristics of respondents

Table 1 sets out the profile of the 200 respondents. Of them, 114 (57.0%) were male, 80 (40.0%) were female and 6 (3.0%) chose not to disclose their gender. Half (50.0%) were in the 25–34 years age group, and the next largest group was 35–44 years (32.5%); just 10.0% were under 25 years and 7.5% were 45 years or older. More than half were married (57.0%). A postgraduate degree was the most common qualification (58.5%), followed by a graduate degree (28.0%) and professional or doctoral qualifications (13.5%). Close to half were employed in the IT and IT-enabled services sector (49.5%), with the rest in BFSI (20.5%), other sectors (15.5%) and pharmaceuticals and life sciences (14.5%). By job level, 52.0% held junior or associate roles, 39.0% were in middle management and 9.0% were in senior management. The largest experience group was 3–7 years (36.0%), and the next was 8–12 years (29.0%). As regards work arrangement, 33.5% worked on-site, 53.0% worked in a hybrid mode and 13.5% worked fully remotely, and 32.0% said they worked night or overlapping shifts for overseas clients. The most common monthly income band was ₹50,000–1,00,000 (40.5%). Overall, the profile mirrors the young, well-educated and largely IT-based nature of the MNC workforce in the Hyderabad region.

Table 1. Socio-demographic and job profile of respondents (N = 200).

Variable	Category	Frequency (%)
Gender	Male	114 (57.0%)
	Female	80 (40.0%)
	Prefer not to say	6 (3.0%)
Age (years)	Below 25	20 (10.0%)
	25–34	100 (50.0%)
	35–44	65 (32.5%)
	45 and above	15 (7.5%)
Marital status	Unmarried	84 (42.0%)
	Married	114 (57.0%)

Variable	Category	Frequency (%)
	Other	2 (1.0%)
Education	Graduate	56 (28.0%)
	Postgraduate	117 (58.5%)
	Professional / doctoral	27 (13.5%)
Sector	IT and IT-enabled services	99 (49.5%)
	BFSI	41 (20.5%)
	Pharma and life sciences	29 (14.5%)
	Others	31 (15.5%)
Job level	Junior / associate	104 (52.0%)
	Middle management	78 (39.0%)
	Senior management	18 (9.0%)
Total experience	Below 3 years	39 (19.5%)
	3–7 years	72 (36.0%)
	8–12 years	58 (29.0%)
	Above 12 years	31 (15.5%)
Work arrangement	On-site	67 (33.5%)
	Hybrid	106 (53.0%)
	Fully remote	27 (13.5%)
Shift pattern	Regular day shift	136 (68.0%)
	Night / overlapping shifts	64 (32.0%)
Monthly income (₹)	Below 50,000	35 (17.5%)
	50,000–1,00,000	81 (40.5%)
	1,00,001–2,00,000	60 (30.0%)
	Above 2,00,000	24 (12.0%)

5.2. Descriptive statistics

Table 2 gives a short overview of the descriptive statistics in terms of the mean and standard deviation scores. Every item mean was near the scale midpoint (2.86–3.07), which points to moderate levels of each construct in the sample. Among the psychological distress items, the highest mean was for 'I feel emotionally drained by my work' (BRN1) (M = 3.04, SD = 1.145), and the next highest was for 'I feel I have little control over the pressures of my job' (OST4) (M = 3.01, SD = 1.110). Of the three distress dimensions, burnout was the strongest (M = 2.99), ahead of occupational stress (M = 2.96) and anxiety and low mood (M = 2.91). Within positive mental health, social well-being had the highest mean (M = 2.98), then psychological functioning (M = 2.96) and emotional well-being (M = 2.92). Work engagement was moderate (M = 2.96); absorption was its strongest dimension (M = 3.00), with dedication (M = 2.97) and vigour (M = 2.92) close behind. The mean scores for individual work productivity (M = 3.00) and organisational productivity (M = 3.01) were almost the same. Every item had a standard deviation above 1.0, so respondents made use of the whole scale, and a sizeable share of employees reported at least moderate distress together with only moderate well-being and engagement.

Table 2. Factor loadings, descriptive statistics and normality measures.

Model constructs and items	FL	M	SD	S	K
Psychological Distress (PSD)					
1. Occupational Stress (OST)		**2.96**	**0.850**	**−0.152**	**−0.368**
OST1 – I feel overwhelmed by the volume of work I am expected to complete	.711	2.94	1.126	−0.062	−0.713
OST2 – I find it difficult to switch off from work-related concerns after office hours	.670	2.96	1.104	0.024	−0.616
OST3 – Tight deadlines and client expectations make me feel tense at work	.657	2.91	1.085	−0.082	−0.667
OST4 – I feel I have little control over the pressures of my job	.640	3.00	1.110	−0.055	−0.568
2. Anxiety and Low Mood (ALM)		**2.91**	**0.895**	**0.096**	**−0.685**
ALM1 – I often feel nervous or on edge during the working day	.652	2.85	1.158	0.090	−0.725
ALM2 – I worry excessively about my job security or performance appraisal	.690	2.89	1.124	0.047	−0.708
ALM3 – I feel low or down-hearted for much of the working week	.652	3.00	1.145	−0.092	−0.708
ALM4 – I have lost interest in work activities I used to enjoy	.715	2.92	1.138	0.085	−0.695
3. Burnout (BRN)		**2.98**	**0.876**	**−0.020**	**−0.642**
BRN1 – I feel emotionally drained by my work	.677	3.04	1.145	−0.150	−0.653
BRN2 – I feel worn out at the end of the working day	.739	2.98	1.114	0.162	−0.674
BRN3 – I feel tired at the thought of another day at work	.655	2.94	1.038	0.084	−0.426
BRN4 – I have become cynical about whether my work contributes anything	.724	2.98	1.167	−0.009	−0.782
Positive Mental Health (PMH)					
4. Emotional Well-being (EWB)		**2.92**	**0.869**	**0.072**	**−0.320**
EWB1 – I feel happy during most of my working days	.652	2.92	1.065	0.070	−0.696
EWB2 – I feel interested in life and in my work	.732	2.94	1.113	0.109	−0.583
EWB3 – I feel satisfied with my life overall	.713	2.90	1.134	0.052	−0.728
5. Psychological Functioning (PFN)		**2.96**	**0.872**	**0.063**	**−0.566**
PFN1 – I feel confident to think and express my own ideas at work	.599	2.99	1.094	0.043	−0.749
PFN2 – I feel good at managing the responsibilities of my daily life	.715	2.86	1.143	0.013	−0.695
PFN3 – I feel my life and work have a sense of direction and meaning	.651	3.04	1.070	−0.030	−0.534
6. Social Well-being (SWB)		**2.98**	**0.875**	**0.050**	**−0.494**
SWB1 – I feel I belong to a community at my workplace	.728	2.96	1.140	0.007	−0.897
SWB2 – I feel people at work are basically good and supportive	.740	2.91	1.122	−0.015	−0.657

Model constructs and items	FL	M	SD	S	K
SWB3 – I feel I have something important to contribute to my organisation and society	.597	3.05	1.036	−0.101	−0.458
Work Engagement (WE)					
7. Vigour (VIG)		**2.92**	**0.846**	**0.019**	**−0.227**
VIG1 – At my work, I feel bursting with energy	.618	2.96	1.081	0.042	−0.619
VIG2 – At my job, I feel strong and vigorous	.674	2.90	1.098	0.039	−0.811
VIG3 – When I get up in the morning, I feel like going to work	.653	2.90	1.037	0.011	−0.466
8. Dedication (DED)		**2.97**	**0.888**	**0.008**	**−0.578**
DED1 – I am enthusiastic about my job	.629	2.96	1.113	−0.021	−0.729
DED2 – My job inspires me	.676	2.98	1.136	0.029	−0.793
DED3 – I am proud of the work that I do	.649	2.98	1.127	0.051	−0.579
9. Absorption (ABS)		**3.00**	**0.862**	**0.115**	**−0.216**
ABS1 – I feel happy when I am working intensely	.621	3.02	1.156	−0.059	−0.775
ABS2 – I am immersed in my work	.674	3.05	1.111	0.012	−0.631
ABS3 – I get carried away when I am working	.652	2.93	1.077	0.067	−0.641
Productivity					
10. Individual Work Productivity (IWP)		**3.00**	**0.848**	**0.033**	**−0.540**
IWP1 – I complete my assigned tasks to the expected quality standard	.653	3.00	1.141	0.010	−0.860
IWP2 – I meet my work targets and deadlines	.465	3.00	1.167	0.086	−0.917
IWP3 – I manage my time so that work is completed on schedule	.718	2.96	1.125	−0.006	−0.762
IWP4 – I can concentrate on my work without frequent loss of focus	.743	3.05	1.133	−0.099	−0.878
11. Organisational Productivity (OP)		**3.01**	**0.794**	**0.102**	**−0.542**
OP1 – My team/department consistently achieves its output targets	.756	2.96	1.100	−0.002	−0.587
OP2 – My organisation delivers projects to clients on time and within budget	.688	3.04	1.038	−0.036	−0.597
OP3 – Absenteeism and unplanned leave are low in my team	.787	3.07	1.077	0.054	−0.627
OP4 – My organisation's overall efficiency and output have improved over the past year	.645	2.96	0.979	−0.137	−0.583

Note: FL – factor loading (varimax-rotated loading of each item on its own factor in the five-factor EFA solution); M – mean; SD – standard deviation; S – skewness; K – kurtosis. Dimension rows report statistics of the dimension mean score. Items OST1–BRN4 are negatively valenced (higher scores indicate greater distress) and were not reverse-coded because they measure the distress construct directly.

5.3. Exploratory factor analysis

To identify the underlying factor structure, an EFA was run before the measurement and structural models were assessed. The hypothesised model had 38 items: 12 for psychological distress, 9 for positive mental health, 9 for work engagement, 4 for individual work productivity and 4 for organisational productivity. Principal Component Analysis with varimax orthogonal rotation was used, since this method makes the solution easier to interpret by producing uncorrelated

components that each, in turn, maximise explained variance (Jolliffe & Cadima, 2016). The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.909, in the 'marvellous' range (Kaiser, 1974), and Bartlett's test of sphericity was significant (χ^2 (703) = 3304.747, $p < 0.001$), showing that the variables were sufficiently correlated. Six components had eigenvalues above 1 (10.487, 3.583, 2.552, 2.271, 1.446 and 1.042). The sixth, however, only just passed the criterion, had no item with a primary loading and had no clear meaning, and the eigenvalues levelled off after the fifth component (1.446, 1.042, 0.939). A five-factor solution was thus retained, and it explained 53.523% of the total variance. This is lower than the 60% guideline often quoted for the social sciences, but values over 50% are accepted for multi-construct behavioural instruments (Hair et al., 2019), and each item loaded on the factor it was meant to measure. Primary loadings ranged between 0.465 (IWP2) and 0.787 (OP3); 37 of the 38 items loaded above 0.50, and no other item showed a cross-loading above 0.40. IWP2 ('I meet my work targets and deadlines') loaded 0.465 on individual work productivity and 0.409 on organisational productivity as a secondary loading. It was kept because of the importance of its content and its acceptable CFA loading (0.663).

The five factors matched the five hypothesised constructs. All twelve items on occupational stress, anxiety and low mood, and burnout loaded together on one psychological distress factor. The nine emotional, psychological and social well-being items loaded on one positive mental health factor, and the nine vigour, dedication and absorption items loaded on one work engagement factor. The other two factors stood for individual work productivity and organisational productivity. In other words, the theorised sub-dimensions did not appear as separate factors; they acted as closely linked facets of three broader constructs. This agrees with the high inter-correlation among the UWES dimensions reported by Schaufeli et al. (2006) and with treating positive mental health as a general well-being factor (Keyes, 2005). Psychological distress explained the most variance (16.415%, rotated eigenvalue = 6.238), followed by positive mental health (12.420%, eigenvalue = 4.719) and work engagement (12.056%, eigenvalue = 4.581) (see Table 3). In Harman's single-factor test, the largest unrotated factor explained 27.6% of the variance, which is under the 50% threshold, and a single-factor CFA fitted the data very poorly (CMIN/DF = 2.674, CFI = 0.611, RMSEA = 0.092). Common method bias was therefore not a serious concern (Podsakoff et al., 2003).

Table 3. Mean, standard deviation, eigenvalues, variance explained and reliability of components.

Latent variable	**Component**	**M**	**SD**	**EV**	**VE (%)**	**α**
Psychological Distress (PSD)	Occupational Stress	2.96	.850	6.238	16.415	0.769
	Anxiety and Low Mood	2.91	.895			0.791
	Burnout	2.98	.876			0.791
Positive Mental Health (PMH)	Emotional Well-being	2.92	.869	4.719	12.420	0.693
	Psychological Functioning	2.96	.872			0.700
	Social Well-being	2.98	.875			0.709
Work Engagement (WE)	Vigour	2.92	.846	4.581	12.056	0.696
	Dedication	2.97	.888			0.696
	Absorption	3.00	.862			0.663
Individual Work Productivity	Individual Work Productivity	3.00	.848	2.243	5.904	0.729
Organisational Productivity	Organisational Productivity	3.01	.794	2.557	6.729	0.751
Total variance explained					**53.523**	

Note: M – mean; SD – standard deviation; EV – rotated eigenvalue and VE – variance explained (%) of the factor in the five-factor solution, shown once per latent variable because the dimensions of each latent variable loaded on one factor; α – Cronbach's alpha of the dimension. Cronbach's α for the overall constructs was 0.912 for PSD, 0.883 for PMH and 0.872 for WE.

5.4. Missing values, outliers and normality

The main distributional assumptions of SEM were checked before the structural model was built and the hypotheses tested (Kline, 2016). None of the 200 responses had missing values. Multivariate outliers were examined through the Mahalanobis distance (D^2). The largest value, 64.126, was lower than the critical χ^2 value of 70.703 (df = 38, p = 0.001), so no case qualified as a multivariate outlier and no case was dropped. Skewness and kurtosis were used to check univariate normality. Item skewness lay between −0.150 and 0.162 and kurtosis between −0.917 and −0.426, comfortably inside the benchmarks of ±2 for skewness and ±7 for kurtosis (Curran et al., 1996; Kim, 2013). Mardia's (1970) coefficient of multivariate kurtosis was −19.118 with a critical ratio of −2.452, under the cut-off of 5.00, so there was no meaningful multivariate non-normality. On the whole, the data were considered suitable for ML-based SEM.

5.5. Multicollinearity

Three checks were made for multicollinearity. The first looked at pairwise correlations. The highest correlation among the five latent constructs was 0.595 (individual work productivity with organisational productivity), and the highest among the dimension scores was 0.783 (emotional with social well-being); both were under the 0.85 threshold proposed by Kline (2016). The second check used the Variance Inflation Factors (VIF) of the three predictors in the structural model (positive mental health, psychological distress and work engagement). These ranged from 1.314 to 1.510, far below the cut-off of 10 (and below the stricter value of 5), and even across all eleven dimension scores the highest VIF was 3.165. In the third check, every tolerance value was above the recommended 0.10 (minimum = 0.662 for the structural predictors) (Hair et al., 2019). Multicollinearity was therefore not an issue, and the data could be taken forward for further analysis.

5.6. Confirmatory factor analysis

CFA was used to assess how the latent variables relate to their observed indicators (Byrne, 2016), and two competing measurement models were compared. Model A included the eleven hypothesised first-order dimensions. Its global fit was acceptable (χ^2 (610) = 669.610, CMIN/DF = 1.098, RMSEA = 0.022, CFI = 0.979), but the estimated correlations between dimensions of the same construct were 0.954–0.971 for the distress dimensions, 0.999–1.095 for the well-being dimensions and 0.982–1.076 for the engagement dimensions. Correlations at or above unity are inadmissible; they show that the dimensions cannot be told apart empirically in this sample, which confirms what the EFA found. Model B included the five constructs, with all the items of a construct loading on a single factor. As seen in Figure 2, each item loaded on just one construct, so the model is a congeneric measurement model (Hair et al., 2019). Model B showed good fit with the data: χ^2 (655) = 712.640, p = 0.059, CMIN/DF = 1.088, RMSEA = 0.021, SRMR = 0.052, CFI = 0.980, IFI = 0.980, TLI = 0.978 (Byrne, 2016; Browne & Cudeck, 1993; Hu & Bentler, 1999). The chi-square difference between the models was not significant ($\Delta\chi^2$ (45) = 43.031, p = 0.556), so merging the eleven dimensions into five constructs did not reduce fit. Model B, being more parsimonious and admissible, was kept. Its standardised factor loadings lay between 0.561 (EWB1) and 0.782 (EWB3) and were all significant at $p < 0.001$; 35 of the 38 loadings were above 0.60, and the other three (EWB1, IWP4 and PFN1) were above 0.55.

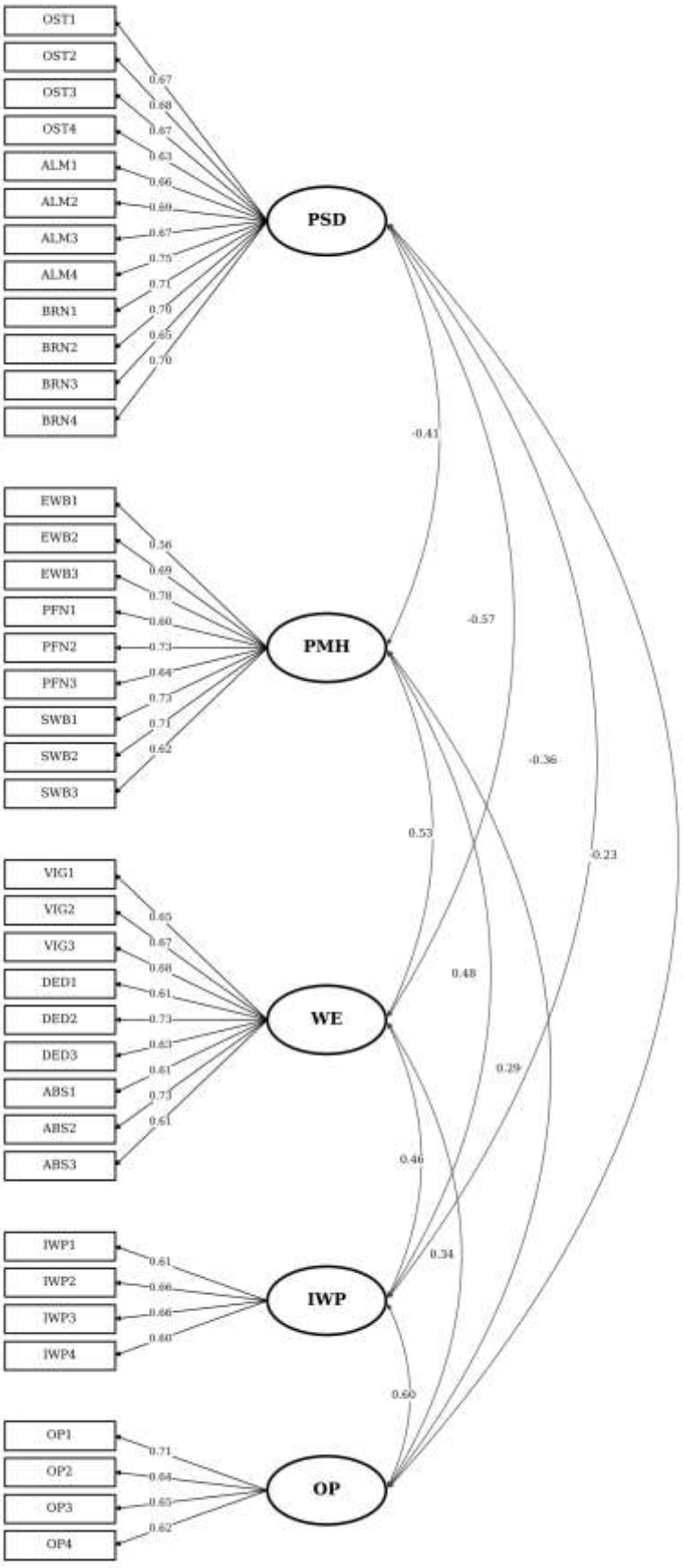


Figure 2. CFA measurement model (Model B: five constructs) with standardised factor loadings and inter-construct correlations.

5.7. Unidimensionality, reliability and validity of the measurement model

Unidimensionality is the degree to which a single underlying factor explains a set of indicators (Hair et al., 2019). Since the EFA showed no significant cross-loadings and the congeneric CFA model had admissible fit, all five constructs were considered unidimensional. Internal consistency was checked with Cronbach's alpha and composite reliability (CR). Cronbach's alpha values were 0.912 for psychological distress, 0.883 for positive mental health, 0.872 for work engagement, 0.751 for organisational productivity and 0.729 for individual work productivity, each above the commonly used threshold of 0.70. At the dimension level (Table 3), alpha ranged from 0.663 for absorption to 0.791 for anxiety and low mood and for burnout. Four three-item dimensions (emotional well-being, vigour, dedication and absorption) fell slightly below 0.70 but stayed above 0.60, a level regarded as acceptable for short scales (Hair et al., 2019). Table 4 shows that the CR values of all five constructs were above 0.70 (0.728–0.912), which confirms construct reliability (Hair et al., 2019).

Convergent validity was evaluated using the factor loadings, CR and the Average Variance Extracted (AVE). Every loading was significant and higher than 0.55, yet the AVE values (0.401–0.464) fell short of the usual benchmark of 0.50 (Table 4). Fornell and Larcker (1981) point out that when AVE is under 0.50 but CR is above 0.60, convergent validity is still adequate, and this criterion has been widely used (Lam, 2012). With CR above 0.72 for every construct, convergent validity was taken as acceptable, though the modest AVE values are noted as a limitation. Discriminant validity was evaluated in three ways. There were, first, no major cross-loadings. Second, the highest inter-construct correlation (0.595, between individual work productivity and organisational productivity) was under 0.85. Third, in line with Fornell and Larcker (1981), each construct's Maximum Shared Variance (MSV) was lower than its AVE, and the square root of each construct's AVE (diagonal values in Table 5) was larger than its correlations with every other construct. As a further check, all heterotrait–monotrait (HTMT) ratios were under 0.85, with the largest at 0.593 (Henseler et al., 2015). The acceptable fit indices of the measurement model (Table 6) lend further support to construct validity.

Table 4. Convergent validity and construct reliability.

Construct	CR	AVE	MSV	MaxR(H)
Psychological Distress (PSD)	0.912	0.464	0.325	0.913
Positive Mental Health (PMH)	0.883	0.458	0.281	0.890
Work Engagement (WE)	0.873	0.434	0.325	0.876
Individual Work Productivity (IWP)	0.728	0.401	0.354	0.730
Organisational Productivity (OP)	0.752	0.432	0.354	0.755

Note: CR – composite reliability; AVE – average variance extracted; MSV – maximum shared variance; MaxR(H) – McDonald construct reliability.

Table 5. Discriminant validity: inter-construct correlations with the square root of AVE on the diagonal (Fornell–Larcker criterion).

	(1)	(2)	(3)	(4)	(5)
(1) PSD	**0.681**				
(2) PMH	−0.413	**0.676**			
(3) WE	−0.570	0.530	**0.658**		
(4) IWP	−0.356	0.476	0.457	**0.633**	
(5) OP	−0.231	0.294	0.340	0.595	**0.657**

Note: bold diagonal values are the square roots of AVE; off-diagonal values are standardised inter-construct correlations from the CFA. PSD – psychological distress; PMH – positive mental health; WE – work engagement; IWP – individual work productivity; OP – organisational productivity.

5.8. Higher-order structure of the mental health and engagement constructs

Under the dual-continua model and the UWES framework, psychological distress, positive mental health and work engagement are higher-order constructs that are reflected in their dimensions. Since the dimensions could not be

separated at the item level (Section 5.6), a standard item-level second-order CFA would not have been admissible, as its second-order loadings would exceed unity. The higher-order structure was therefore tested with a dimension-level model, in which the mean score of each dimension acted as an indicator (parcel) of its higher-order construct (Little et al., 2002). Occupational stress, anxiety and low mood, and burnout served as indicators of psychological distress; emotional, psychological and social well-being of positive mental health; and vigour, dedication and absorption of work engagement. Individual work productivity and organisational productivity kept their item indicators. Figure 3 shows that the dimensions loaded strongly on their higher-order constructs, with standardised loadings from 0.813 (psychological functioning → PMH) to 0.889 (social well-being → PMH), all significant at $p < 0.001$. Fit was very good: χ^2 (109) = 99.008, p = 0.743, CMIN/DF = 0.908, RMSEA = 0.000, SRMR = 0.038, CFI = 1.000, TLI = 1.008 (Byrne, 2016; Hu & Bentler, 1999). The results confirm that the dimensions are strong and coherent facets of the three higher-order constructs, and this supports modelling psychological distress, positive mental health and work engagement as single constructs in the structural model.

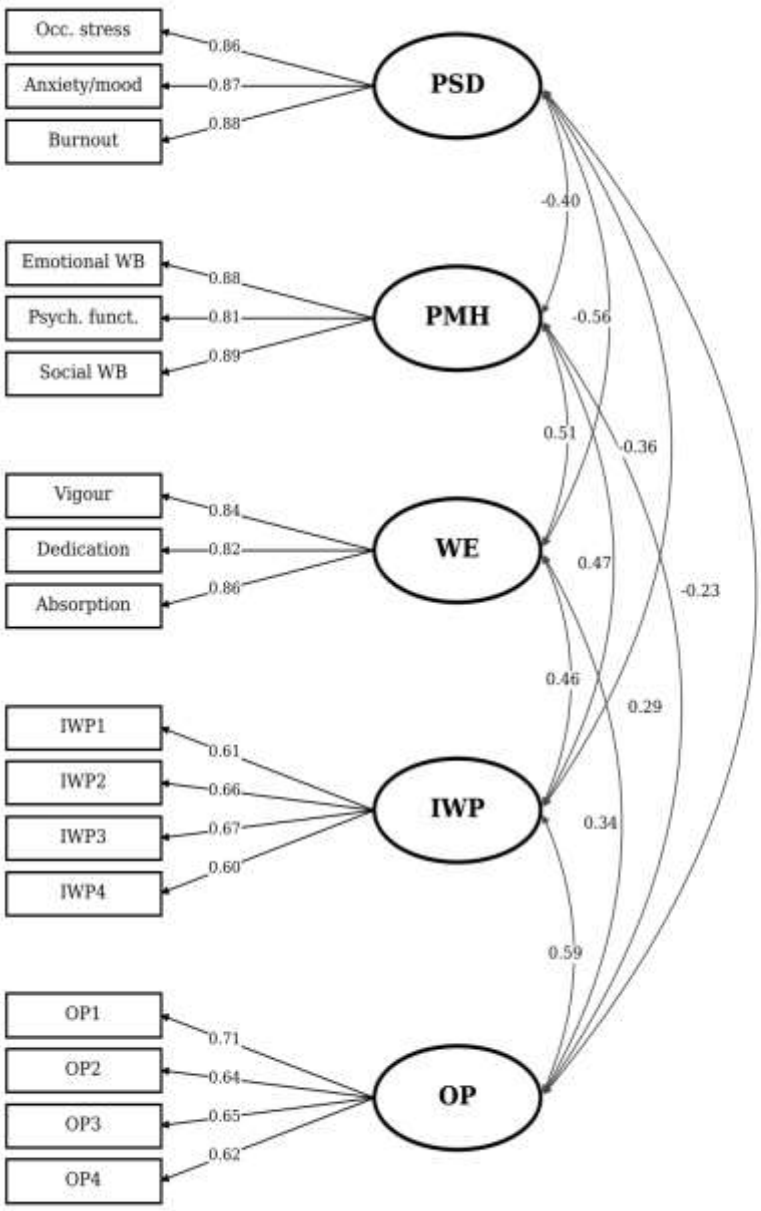


Figure 3. Dimension-level (higher-order) measurement model with standardised loadings and inter-construct correlations.

5.9. Structural model and hypothesis testing

Once missing values, outliers, normality, multicollinearity, unidimensionality, reliability, validity and model fit had been assessed, the hypothesised relationships among the five constructs were tested with the MLE method of SEM. Table 6 reports the absolute, incremental and parsimony fit indices of the structural model, all of which were admissible: χ^2 (656) = 737.956, p = 0.014, CMIN/DF = 1.125, RMSEA = 0.025, SRMR = 0.058, CFI = 0.971, TLI = 0.969, IFI = 0.972, PNFI = 0.740, PGFI = 0.702 and PCLOSE = 1.000 (Bentler, 1990; Browne & Cudeck, 1993; Hu & Bentler, 1999; Kline, 2016). The chi-square statistic was significant, which often happens with samples of this size and models with many indicators, so fit was judged using the normed chi-square and the other indices (Hair et al., 2019). The structural model has one degree of freedom more than the measurement model, because, as hypothesised, no direct relationship was specified between the two productivity outcomes.

Table 6. Fit indices of the measurement and structural models.

Indices of fit	**Index**	**Measurement model**	**Structural model**	**Acceptable range**	**Source**
Absolute	Chi-square (CMIN)	712.640 (df = 655)	737.956 (df = 656)	p > 0.05	Byrne (2016)
	RMSEA	0.021	0.025	< 0.08	Browne & Cudeck (1993)
	SRMR	0.052	0.058	< 0.08	Hu & Bentler (1999)
Incremental	CFI	0.980	0.971	> 0.90	Bentler (1990)
	TLI	0.978	0.969	> 0.90	Hu & Bentler (1999)
	IFI	0.980	0.972	> 0.90	Hu & Bentler (1999)
Parsimony	PNFI	0.745	0.740	> 0.50	Hair et al. (2019)
	PGFI	0.707	0.702	> 0.50	Hair et al. (2019)
	CMIN/DF	1.088	1.125	< 3	Kline (2016)
	PCLOSE	1.000	1.000	> 0.05	Browne & Cudeck (1993)

Note: RMSEA – root mean square error of approximation; SRMR – standardised root mean square residual; CFI – comparative fit index; TLI – Tucker–Lewis index; IFI – incremental fit index; PNFI – parsimony normed fit index; PGFI – parsimony goodness-of-fit index; CMIN/DF – normed chi-square; PCLOSE – closeness of fit.

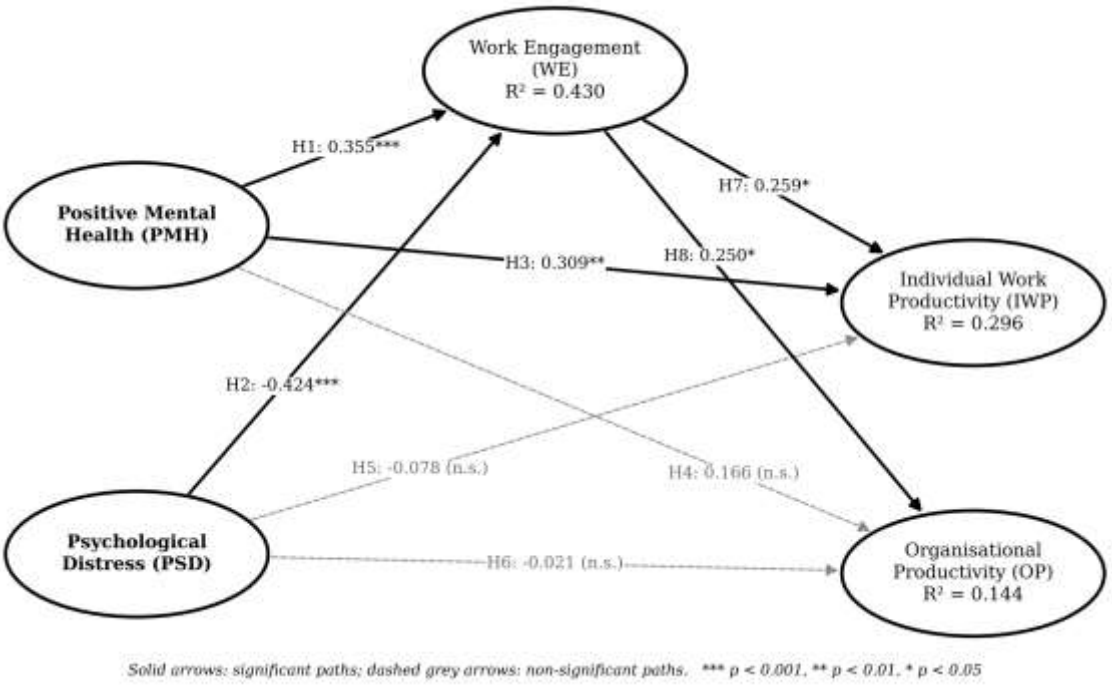


Figure 4. Structural model with standardised path coefficients and R^2 values.

5.10. Direct, indirect and total effects

With the overall structural model validated, the hypothesised relationships among the constructs were tested. The path analysis (Figure 4, Tables 7 and 8) showed that positive mental health had a positive and significant effect on work engagement ($\beta = 0.355$, C.R. = 4.068, $p < 0.001$), so H1 was supported. Psychological distress had a negative and significant effect on work engagement ($\beta = -0.424$, C.R. = −4.895, $p < 0.001$), so H2 was supported; of the two predictors of engagement, distress was the stronger. Turning to the direct effects on productivity, positive mental health significantly predicted individual work productivity ($\beta = 0.309$, C.R. = 2.874, $p = 0.004$; H3 supported), but it did not predict organisational productivity ($\beta = 0.166$, C.R. = 1.603, $p = 0.109$; H4 not supported). Psychological distress had no significant direct effect on either individual work productivity ($\beta = -0.078$, C.R. = −0.779, $p = 0.436$; H5 not supported) or organisational productivity ($\beta = -0.021$, C.R. = −0.201, $p = 0.840$; H6 not supported). Work engagement had a positive and significant influence on individual work productivity ($\beta = 0.259$, C.R. = 2.211, $p = 0.027$; H7 supported) as well as on organisational productivity ($\beta = 0.250$, C.R. = 2.086, $p = 0.037$; H8 supported).

Next, the indirect relationships were examined. The mediating role of work engagement between the two mental health dimensions and the two productivity outcomes was tested using bias-corrected bootstrapping with 5,000 resamples (Preacher & Hayes, 2008). An indirect effect is significant when zero does not lie between the lower and upper limits of the 95% confidence interval (Zhao et al., 2010). Table 9 shows that the indirect effect of positive mental health on individual work productivity through work engagement was significant ($\beta = 0.092$, 95% CI [0.011, 0.206], $p = 0.031$), which supports H9. The indirect effect of positive mental health on organisational productivity was also significant ($\beta = 0.089$, 95% CI [0.009, 0.202], $p = 0.043$), which supports H10. Psychological distress likewise had significant indirect effects on individual work productivity ($\beta = -0.110$, 95% CI [−0.228, −0.014], $p = 0.031$) and on organisational productivity ($\beta = -0.106$, 95% CI [−0.234, −0.008], $p = 0.043$), supporting H11 and H12. The type of mediation was determined by comparing direct and indirect effects. When both were significant, the mediation was classed as partial (complementary), and when only the indirect effect was significant, it was classed as full (indirect-only) (Zhao et al., 2010). On this basis, work engagement partially mediated the effect of positive mental health on individual work productivity, where the direct effect stayed significant, and fully mediated the remaining three relationships, where the direct effects were not significant. The total effects (Table 7) indicate that positive mental health had a considerable overall influence on individual ($\beta = 0.401$, $p < 0.001$) and organisational productivity ($\beta = 0.255$, $p = 0.010$). Psychological distress had a significant total effect on individual work productivity ($\beta = -0.188$, $p = 0.044$), whereas its

total effect on organisational productivity was not significant (β = −0.127, p = 0.237). The indirect effect in this second case still matters, because mediation does not require a significant total effect (Zhao et al., 2010).

Table 7. Direct, indirect and total effects of the structural model.

Independent (exogenous) variables	**Work engagement**	**p**	**Individual work productivity**	**p**	**Organisational productivity**	**p**
Positive Mental Health						
Direct effect	0.355	< 0.001	0.309	0.004	0.166	0.109
Indirect effect	N.A.	N.A.	0.092	0.031	0.089	0.043
Total effect	0.355	< 0.001	0.401	< 0.001	0.255	0.010
Psychological Distress						
Direct effect	−0.424	< 0.001	−0.078	0.436	−0.021	0.840
Indirect effect	N.A.	N.A.	−0.110	0.031	−0.106	0.043
Total effect	−0.424	< 0.001	−0.188	0.044	−0.127	0.237
Work Engagement						
Direct effect	N.A.	N.A.	0.259	0.027	0.250	0.037
Indirect effect	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Total effect	N.A.	N.A.	0.259	0.027	0.250	0.037
R^2 (squared multiple correlation)	**0.430**		**0.296**		**0.144**	

Note: standardised estimates; p-values for indirect and total effects from bias-corrected bootstrapping (5,000 resamples). N.A. – not applicable.

Table 8. Summary of results of the direct relationships among constructs.

Hypothesis	**Path**	**β estimate**	**S.E.**	**C.R.**	**p**	**Remark**
H1	WE ← PMH	0.355	0.102	4.068	***	Supported
H2	WE ← PSD	−0.424	0.080	−4.895	***	Supported
H3	IWP ← PMH	0.309	0.125	2.874	0.004 **	Supported
H4	OP ← PMH	0.166	0.138	1.603	0.109	Not supported
H5	IWP ← PSD	−0.078	0.092	−0.779	0.436	Not supported
H6	OP ← PSD	−0.021	0.110	−0.201	0.840	Not supported
H7	IWP ← WE	0.259	0.116	2.211	0.027 *	Supported
H8	OP ← WE	0.250	0.136	2.086	0.037 *	Supported

Note: *** p < 0.001; ** p < 0.01; * p < 0.05. β – standardised estimate; S.E. and C.R. refer to the unstandardised estimate. PMH – positive mental health; PSD – psychological distress; WE – work engagement; IWP – individual work productivity; OP – organisational productivity.

Table 9. Bootstrapped mediation analysis (indirect effects through work engagement).

Hypothesis	Indirect path	Indirect effect (β)	Lower bound	Upper bound	p	Type of mediation
H9	PMH → WE → IWP	0.092	0.011	0.206	0.031	Partial
H10	PMH → WE → OP	0.089	0.009	0.202	0.043	Full
H11	PSD → WE → IWP	−0.110	−0.228	−0.014	0.031	Full
H12	PSD → WE → OP	−0.106	−0.234	−0.008	0.043	Full

Note: standardised indirect effects; bias-corrected 95% confidence intervals based on 5,000 bootstrap samples. Partial – complementary mediation (direct and indirect effects both significant); Full – indirect-only mediation (direct effect not significant) (Zhao et al., 2010). All four hypotheses (H9–H12) are supported because no confidence interval contains zero.

6. Discussion

An important result of this study is how much of the variance in the endogenous variables their predictors explain, as shown by the squared multiple correlation (R^2) (Byrne, 2016). Figure 4 shows that positive mental health and psychological distress explained 43.0% of the variance in work engagement. Along with work engagement, the two mental health dimensions explained 29.6% of the variance in individual work productivity and 14.4% of the variance in organisational productivity. The weaker explanation of organisational productivity is not surprising, since output at the organisation level also depends on technology, processes, leadership and market conditions, none of which are part of the model.

Both dimensions of mental health turned out to be strong determinants of work engagement among MNC employees in Telangana. Employees who feel emotionally positive, purposeful and socially connected bring more energy, enthusiasm and concentration to what they do. This agrees with the broaden-and-build theory (Fredrickson, 2001) and with earlier findings that psychological well-being drives engagement (Robertson et al., 2012; Shuck & Reio, 2014). Psychological distress reduced engagement, and this negative effect was a little larger than the positive effect of well-being (β = −0.424 versus 0.355). The result supports the health-impairment process of the JD–R model, under which chronic stress and exhaustion use up the resources people need to engage (Bakker et al., 2014; Hakanen et al., 2008; Hobfoll, 1989). The two mental health dimensions appeared as distinct, moderately correlated predictors (r = −0.413) and not as two ends of a single scale. This gives empirical support to the dual-continua model (Keyes, 2002, 2005) in an Indian corporate setting. Put simply, lowering distress is not enough by itself to create an engaged workforce, and promoting well-being on its own does not cancel out the effects of distress.

A second major finding relates to the direct effects of mental health on productivity, which were narrower than hypothesised. Positive mental health directly improved individual work productivity, as Wright and Cropanzano (2000, 2004) and the meta-analysis of Ford et al. (2011) would predict, but it had no significant direct effect on organisational productivity. Contrary to what was expected, psychological distress showed no direct effect on individual or organisational productivity after work engagement and positive mental health were accounted for. This should not be read as saying that distress does no harm to productivity. Distress was negatively correlated with both outcomes (r = −0.356 with individual and −0.231 with organisational productivity), and its total effect on individual work productivity was significant (β = −0.188). What the result shows is that the productivity cost of distress travels through the loss of engagement and not through a direct route. Such a pattern makes sense in MNCs, where team structures, process controls and the redistribution of workload can cover the lower output of distressed individuals for a while, although the engagement of the wider team suffers as a result. It also fits research showing that productivity losses linked to distress and burnout come mostly from lower energy and concentration on the job, that is, presenteeism (Johns, 2010; Taris, 2006; Bubonya et al., 2017).

Work engagement was also found to have a positive and significant influence on both productivity outcomes, which supports the meta-analysis of Christian et al. (2011) and the unit-level findings of Harter et al. (2002) and Salanova et al. (2005). Engagement had a similar effect on individual work productivity (β = 0.259) and organisational productivity

(β = 0.250). This suggests that employees' vigour, dedication and absorption carry over into their own output and also into how the performance of their teams and organisations is perceived.

The mediation analysis confirmed work engagement as the psychological mechanism that converts mental health into productivity. Engagement played a partial mediating role between positive mental health and individual work productivity; well-being therefore raises an employee's own output both directly and by way of engagement. In the other three relationships, namely positive mental health with organisational productivity and psychological distress with both productivity outcomes, the mediation was full, so these effects work only through engagement. This matters most for distress, since its damage to productivity does not show up in a direct-effects analysis and only becomes clear when the engagement pathway is modelled. The findings support the combined motivational and health-impairment processes put forward by JD–R theory (Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004), and they carry the mediating role of engagement reported by Saks (2006) and Rich et al. (2010) over to mental health as an antecedent.

6.1. Theoretical implications

The study adds to theory in four ways. To begin with, it brings the dual-continua model into the study of productivity and shows that positive mental health and psychological distress each contribute separately to work outcomes, which means future research on employee mental health ought to measure both. In addition, it links the dual-continua model with JD–R theory by showing that well-being works through the motivational process and distress through the health-impairment process, with work engagement as the shared pathway to productivity. The study also models individual and organisational productivity as separate constructs, and in doing so shows that the effects of mental health reach beyond the individual employee to the organisation, partly by different routes. Lastly, it offers structural evidence from Indian MNC employees, a large and expanding workforce that is still under-represented in the mental health–productivity literature, and confirms that the model is admissible under the MLE method of SEM.

6.2. Managerial implications

The results have clear implications for HR leaders and managers of MNCs in Telangana. To start with, psychological distress was the strongest single cause of disengagement and, by that route, lowered both individual and organisational productivity, so organisations should see workload management as a productivity matter. Setting realistic deadlines, staffing in line with project demands, rotating night and overlapping shifts, and laying down clear norms on after-hours communication can all cut the demands that lead to distress. In addition, because positive mental health drives engagement and individual productivity independently, wellness initiatives should go beyond managing illness. Programmes that build purpose, autonomy, belonging and recognition, for instance meaningful career conversations, peer support communities and participative decision-making, help to strengthen the well-being continuum.

Work engagement should also be tracked as a leading indicator of productivity. Regular pulse surveys of engagement, run together with measures of distress, make it possible to step in early, before productivity falls. Managers, moreover, are the most direct lever available. Training line managers to spot signs of distress, hold supportive conversations and refer employees to Employee Assistance Programmes is in line with WHO's recommendations on mental health at work (WHO, 2022; WHO & ILO, 2022) and with evidence on workplace interventions that work (Joyce et al., 2016; LaMontagne et al., 2014). At the policy level, the Government of Telangana and industry bodies can encourage MNCs to adopt workplace mental health standards and to report on well-being, which would help the state keep its competitive advantage in skilled talent.

7. Conclusion

Keeping Telangana's MNC workforce productive is vital for the state's economic growth and for its standing as a global business destination. This study examined the structural relationships among employees' mental health, work engagement and productivity in a sample of 200 MNC employees in Telangana, using a validated model estimated through the MLE method of SEM. The exploratory and confirmatory analyses showed that the theorised dimensions of psychological distress (occupational stress, anxiety and low mood, and burnout), positive mental health (emotional, psychological and social well-being) and work engagement (vigour, dedication and absorption) behaved as closely related facets of three higher-order constructs. CFA confirmed that a five-construct measurement model was reliable

and valid, and the dimension-level model supported the higher-order structure of the mental health and engagement constructs.

According to the structural model, positive mental health strengthens work engagement and psychological distress weakens it, and engagement then drives individual and organisational productivity. Positive mental health had a direct effect on individual work productivity as well. By contrast, the effects of psychological distress on both productivity outcomes, and the effect of positive mental health on organisational productivity, passed wholly through work engagement. Work engagement is thus the mechanism by which mental health turns into productive effort. The study concludes that employee mental health is a strategic determinant of organisational productivity in MNCs, and that money spent on reducing distress and building well-being is best understood as an investment in performance.

7.1. Limitations and future studies

Several limitations of the study should be noted. Its cross-sectional design restricts causal inference, and longitudinal or diary designs would show more clearly how mental health and productivity change over time. The sample of 200 respondents satisfies the minimum recommended for SEM, but it is modest for a model of this size; larger samples would make multi-group analysis possible by sector, gender, job level or work arrangement. Because non-probability sampling was used, the findings cannot be generalised far beyond the MNC employees studied. All variables were self-reported by the same respondents, so common method bias cannot be completely ruled out even after procedural and statistical checks; future work should pair self-reports with supervisor ratings or objective productivity indicators such as utilisation, absence records and output metrics. The distress measures are screening items and not clinical diagnoses. In addition, the sub-dimensions of distress, well-being and engagement could not be separated empirically, the AVE values of the constructs were under 0.50, and the five-factor EFA solution explained 53.5% of the variance. Future studies should therefore use longer validated instruments (for example, the full MHC-SF, DASS-21 and UWES-17) so that the dimensions can be modelled one by one. Further research could also add moderators such as perceived organisational support, leadership style, remote working and digital overload, and could extend the study to MNCs in other Indian states for comparison.

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